



# Techno-economic analysis of household and community energy storage for residential prosumers with smart appliances



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## HIGHLIGHTS

- Modelling and optimization of HES and CES for prosumers with smart appliances.
- Economic feasibility of both HES and CES using real data of 39 households in a pilot project.
- Sensitivity analysis considering different sizes and prices of storage systems.
- PV self-consumption has a large impact on annual saving achieved by storage and influences the PBP.
- Under current investment costs of storage, both HES and CES are economically infeasible.

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## ABSTRACT

The emergence of Decentralized Energy Resources (DERs) and rising electricity demand are known to cause grid instability. Additionally, recent policy developments indicate a decreased tariff in the future for electricity sold to the grid by households with DERs. Energy Storage Systems (ESS) combined with Demand Side Management (DSM) can improve the self-consumption of Photovoltaic (PV) generated electricity and decrease grid imbalance between supply and demand. Household Energy Storage (HES) and Community Energy Storage (CES) are two promising storage scenarios for residential electricity prosumers. This paper aims to assess and compare the technical and economic feasibility of both HES and CES. To do that, mathematical optimization is used in both scenarios, where a Home Energy Management System (HEMS) schedules the allocation of energy from the PV system, battery and the grid in order to satisfy the power demand of households using a dynamic pricing scheme. The problem is formulated as a Mixed Integer Linear Programming (MILP) with the objective of minimizing the costs of power received from the grid. Data from real demand and PV generation profiles of 39 households in a pilot project initiated by the Distribution System Operator (DSO) 'Enexis' in Breda, the Netherlands, is used for the numerical analysis. Results show that the self consumption of PV power is the largest contributor to the savings obtained when using ESS. The implementation of different ESS reduces annual costs by 22–30% and increases the self-consumption of PV power by 23–29%. Finally, a sensitivity analysis is performed which shows how investment costs of ESS per kWh are crucial in determining the economic feasibility of both systems.

## 1. Introduction

Over the last couple of decades, global power demand has increased significantly across all sectors [1]. In the residential sector, electrification is an important contributor to the increasing power demand [2]. At the same time, both European and Dutch national policy dictate that efforts should be made to reduce carbon emissions and increase the share of renewable energy in order to counter climate change [3,4]. This has led to the rapid development and application of renewable energy technologies. In the residential sector, this trend has manifested itself by a sharp increase of Photovoltaic (PV) systems on residential rooftops.

The intermittent nature of Decentralized Energy Resources (DERs), combined with the rising electricity demand causes difficulties for the grid operator in maintaining the grid's reliability and stability. The peak demand of electricity usually occurs at a different interval from the supply peak provided by DERs, creating a mismatch between renewable generation profiles and demand profiles [5]. Demand Side Management (DSM) is one of the concepts used to optimize the matching between power supply and demand. DSM is defined as 'actions that influence the way consumers use electricity in order to achieve savings and higher efficiency in energy use' [6]. DSM can be used to optimize self-consumption levels of DERs, thereby decreasing the need for energy

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**Nomenclature****Abbreviations**

CES	community energy storage
DER	decentralized energy resource
DSM	demand side management
DSO	distribution system operator
EMS	energy management system
ESS	energy storage systems
HEMS	home energy management system
HES	household energy storage
LCOE	levelized cost of energy
MILP	mixed integer linear programming
PBP	pay back period
PHEV	plug-in hybrid electric vehicle
PV	photovoltaic
RES	renewable energy sources
RTP	real time pricing
S1PW1	scenario1: HES with Powerwall 1
S1PW2	scenario1: HES with Powerwall 2
S2CES	scenario2: CES with current operating size
S2CESopt	scenario2: CES with optimal size
SoC	state of charge
WM	washing machine

**Indices**

$a$	index for shiftable appliances, $a \in \{1,2,\dots,A\}$
$i$	index for households, $i \in \{1,2,\dots,N\}$
$t$	index for time-slots, $t \in \{1,2,\dots,T\}$

**Sets**

$A^i$	number of shiftable appliances in household $i$
$N$	number of households
$T$	number of time-slots for the considered time horizon

**Parameters**

$\eta_{ch}$	battery charging efficiency [-]
$\eta_{dis}$	battery discharging efficiency [-]
$C_{bat,CES}^i$	battery share size of the CES allocated to $i$ [kWh]
$C_{bat,HES}^i$	battery capacity of the HES in $i$ [kWh]
$c^t$	cost of power absorbed from the grid at $t$ [Euro/kWh]
$Cap_{CES}^i$	optimal battery share size for $i$ [kWh]
$Cap_{CES,opt}$	optimal size of CES [kWh]
$CP^{a,t,i}$	consumer preference for the activation of $a$ in $i$ at $t$ (i.e., on or off)

$E_{sl}^a$	daily energy consumption requirement of $a$ [kWh]
$E_{grid,inj}^i$	maximum daily injected energy to the grid the battery should be able to store in $i$ [kWh]
$P_{peak}^{t,i}$	maximum allowed power for $i$ in each $t$ [kW]
$P_{max}^a$	upper limit of power assignment to $a$ [kW]
$P_{min}^a$	lower limit of power assignment to $a$ [kW]
$P_{bat,max}^i$	maximum power that can charge/discharge the battery in $i$ [kW]
$P_{grid,max}^i$	maximum allowed power from/to grid in $i$ [kW]
$P_{nsl}^{t,i}$	non-shiftable load in household $i$ at $t$ [kW]
$r^a$	number of time-slots $a$ should run before it can be switched off
$Sh^i$	household $i$ share of the CES [%]
$SoC_{max}$	maximum battery SoC [%]
$SoC_{min}$	minimum battery SoC [%]
$SoC_0$	initial battery SoC [%]

**Variables**

$p^{a,t,i}$	power demand of $a$ in $i$ at $t$ [kWh]
$p^{t,i}$	power action in $i$ at $t$ [kW]
$P_{bat,ch}^{t,i}$	battery charging power in $i$ at $t$ [kW]
$P_{bat,dis}^{t,i}$	battery discharging power in $i$ at $t$ [kW]
$P_{grid,abs}^{t,i}$	power absorption from the grid in $i$ at $t$ [kW]
$P_{grid,inj}^{t,i}$	power injection to the grid from $i$ at $t$ [kW]
$P_{pv}^{t,i}$	power harvested by the local PV system of $i$ at $t$ [kW]
$P_{sl}^{t,i}$	shiftable load in $i$ at $t$ [kW]
$SoC^{t,i}$	battery state of charge in $i$ at $t$ [%]
$y^{a,t,i}$	a binary decision variable indicates whether $a$ at $t$ in $i$ is on (1) or off (0)
$z^{a,i}$	a binary decision variables indicates when $a$ starts operating in $i$

**Economic indicators**

$\gamma$	discount rate [%]
$C_{annual}^i$	annual costs of electricity in $i$ [Euro]
$I_{CES}$	investment cost in CES [Euro]
$I_{HES}$	investment cost in HES [Euro]
$L$	lifetime of storage system [years]
$LCOE^i$	levelized costs of electricity for $i$ [Euro/kWh]
$PBP_{CES}^i$	number of years before the investment in CES is recovered for $i$ [years]
$PBP_{HES}^i$	number of years before the investment in HES is recovered for $i$ [years]
$S^i$	costs savings per year of power absorbed from the grid after and before using the storage [%]

transportation across the grid. DSM is most promising for controllable and shiftable load, such as Plug-in Hybrid Electric Vehicle (PHEV) and flexible appliances, which can be run at flexible time schedules in the scope of a day [5]. However, not all household load is suitable for DSM. Some appliances are either bound to a specific time of use (e.g., cooking) or provide low capabilities for shifting power consumption for relatively long time periods (e.g., cold appliances). Other appliances do not use significant amounts of energy to be suitable for DSM (e.g., electronics). Therefore, it is almost impossible to match all households electricity demand with the available supply at a certain time.

Energy Storage Systems (ESS) can be used as a complementary solution to improve the self-consumption of electricity generated by DERs [7,8]. Surplus energy can be stored temporarily in a Household Energy Storage (HES) to be used later as a supply source for residential demand

[9]. The battery can also be used to react on price signals [10]. When the price of electricity is low, the battery can be charged. When the price is high, the battery can be discharged and make profit by selling electricity back to the grid. However, ESS costs have been identified as a possible downside of residential battery exploitation [11,12]. Currently it might not be possible to earn back the investment costs of the battery since selling back energy to the grid can be more profitable. In the Netherlands, the feed-in tariff for electricity generated by DERs is identical to the electricity price, therefore there is no incentive for household to deploy a HES system [13].

Recent policy developments indicate a decreased tariff in the future for electricity sold back to the grid by households with DERs [4]. Therefore, self-consumption is becoming more attractive for households in order to improve the 'financial utilization' of their PV system. By

increasing the self-consumption of PV-generated electricity, costs of absorbing electricity from the grid are avoided.

The integration of both DSM and ESS to improve the self-consumption has recently gained increased attention in literature. In [6], a PV system, combined with ESS and DSM, has been simulated and subsequently tested in reality. The combination of DSM and ESS showed considerable improvement of the self-consumption of PV-generated electricity. Another study demonstrated the potential of a similar system combined with a PHEV [14]. It has been found that the utility could effectively control the peak load and as a consequence, the consumer satisfaction is compromised because of supply curtailment by the utility. This led to a shortage in power supply for some consumers. In [15], a user-centric Home Energy Management System (HEMS) is used in combination with a local ESS and smart appliances. The HEMS is used to determine the optimal day-ahead scheduling of household smart appliances, charging and discharging of the battery and power absorption from PV and the grid. A HEMS for households with ESS, PV and electric vehicle is presented in [16], where the effects of sequential uninterruptible energy phases of electric appliances is considered in the day-ahead scheduling.

Community Energy storage (CES) is another application of ESS which is seen as a promising option for managing power demand and DERs supply. In [17], CES is referred to as 'ESS located at the consumption level with the ability to perform multiple applications with a positive impact for both the consumer as the Distribution System Operator (DSO)'. Research has shown that CESs may offer additional benefits compared to HESs like economies of scale, energy trading and enhanced grid balancing capabilities [18,19]. A CES with a centralized Energy Management System (EMS) is proposed in [20]. The EMS manages the CES and controls the allocation of available energy in the storage unit to households. In this system, several households, with DERs, share a single CES system. Results show that using this system, self-consumption and cost savings can be increased significantly. In [21], a framework enabling users with DERs to trade energy with a CES is proposed. A dynamic non-cooperative repeated game model is employed to optimize the energy trading amounts of users for the next day. A predictive day-ahead smart charging mechanism of CES based on Markov chains is proposed in [22]. The study shows that the CES can achieve higher cost savings and self-consumption levels but it does not discuss the individual benefit for each household. In [23], the economic benefits of both Li-ion and Pb-acid batteries in CES units are compared. Results show that Pb-acid batteries requires a larger storage capacity in order to reduce costs.

These studies show that costs savings and higher self-consumption levels can be achieved when using ESS. However, a detailed economic analysis which compares both HES and CES systems using real data, is still missing. This paper aims to assess and compare the techno-economical performance of both HES and CES from the perspective of the end-consumer. In order to illustrate the impact of future developments,

such as the policy developments presented earlier, a sensitivity analysis will be conducted. To achieve this goal, both HES and CES systems will be modelled in an optimization framework. Data input for the models is obtained from a pilot project in a residential district, currently being conducted by the Dutch DSO 'Enexis'.

The rest of the paper is organized as follows. The system model is presented in Section 2. The optimization problem formulation is presented in Section 3. Section 4 presents the economic indicators. Numerical evaluation and sensitivity analysis are performed in Section 5. Section 6 discusses the work and gives pointers for future research. Finally, the paper is concluded in Section 7.

## 2. System model

### 2.1. Assumptions

In this work we consider a set of households  $\mathcal{N}$ , indexed by  $i \in \{1, 2, \dots, N\}$ , whose electricity demand can be satisfied by a grid connection, a rooftop PV system installation and a storage system. Households are connected to the main grid via AC power lines. A household electricity power demand is represented by a load profile. The load profile is divided into two parts, a non-shiftable and a shiftable load profile. The non-shiftable load is inflexible and can not be controlled. This shiftable load can be scheduled to time-slots with more favourable price conditions. Favourable price conditions occur when either the grid power price is low, or power can be drawn from the PV system or the ESS. The PV generation profile for each household is obtained from smart meter measurements at each time-slot, resulting in a generation profile. Each household is equipped with the same panel type, while the PV installations can differ in size and orientation between households.

We assume that households' demands are variable both in quantity and time. After satisfying the demand using the locally installed PV system, each household at a certain time period could either have a surplus amount of PV-generated energy, or request energy for its residual demand. The average power action of household  $i$  happens on a time-slot  $t \in \mathcal{T} = \{t_0, t_0 + \Delta t, t_0 + 2\Delta t, \dots, T\}$ , and denoted as  $p^{t,i}$ . Each time-slot can represent different timing horizons (e.g., an hour). In this way, the energy is represented by the average power during a time-slot of length  $\Delta t$  (i.e.,  $E = p\Delta t$ ). A power action of household  $i$  at time-slot  $t$  could be either an interaction with the main grid (i.e., injection  $p_{grid,inj}^{t,i}$  or absorption  $p_{grid,abs}^{t,i}$ ), or an interaction with the battery (i.e., charging  $p_{bat,ch}^{t,i}$  or discharging  $p_{bat,dis}^{t,i}$ ), where  $p_{grid,inj}^{t,i}, p_{grid,abs}^{t,i}, p_{bat,ch}^{t,i}$  and  $p_{bat,dis}^{t,i} \in \mathbb{R}$ .  $p_{grid,inj}^{t,i}$  is introduced to allow households to inject the excessive power into the main grid in case the battery is fully charged. The amount of power harvested by the local PV system of household  $i$  at time-slot  $t$  is  $p_{pv}^{t,i}$ . Two different scenarios of ESS are distinguished in this paper, (i) a HES and (ii) a CES.

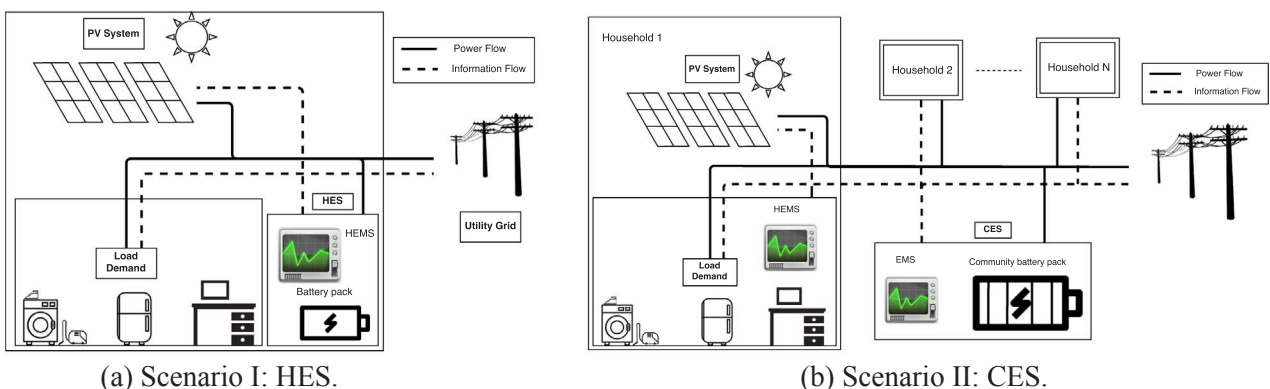


Fig. 1. System architecture of the ESS scenarios.

## 2.2. Scenario I: HES

In this scenario, each household is equipped with a HES that consists of a battery pack and a HEMS. The battery can be used to store surplus PV power. Alternatively, the HES is also permitted to store electricity purchased from the grid. The HEMS is located within a household and operates autonomously to minimize the costs of the total power demand. The system architecture of scenario I is illustrated in Fig. 1(a).

## 2.3. Scenario II: CES

In this scenario, the  $N$  households are connected to a CES, where they can store their surplus power from the PV system. Alternatively, the CES can also be charged from the grid. The CES consists of a large battery, which can be divided into shares, and an EMS. The CES is assumed to be owned and operated by a utility company. Households are allocated a certain share of the battery. Both the battery and the households are connected to the grid via AC power lines. The EMS has to be able to communicate with the households, therefore a separate data connection is required between households and the EMS. Each household is equipped with a HEMS which controls the flexible load. It also schedules the battery share and the use of PV power to satisfy demand. The HEMSs communicate with the EMS about the total power demand and surplus PV production to ensure that it does not exceed the maximum charging and discharging capacity of the CES. The system architecture of scenario II is illustrated in Fig. 1(b).

In both scenarios the HEMS receives additional information from the household and from the utility. From the household, the HEMS receives some input parameters about the number of shiftable appliances that can be scheduled in household  $i$  ( $A^i$ ), and the time preference for the activation of those appliances ( $CP^{a,i}$ ). The utility sends the time varying electricity price signal ( $c^t$ ), and the maximum allowed power in each time-slot ( $P_{peak}^{t,i}$ ). Other constant input data, such as power boundaries and total power demand of each appliance, can be stored in the database of the HEMS. Using these data, the HEMS calculates the set-points power of the battery and provides the optimal schedules of power demand for each household.

## 2.4. Battery shares of CES

Since power demand and generation differs between households, the required storage capacity to minimize costs at the CES is different for each household. Therefore, the battery is divided into shares based on known statistics from each household. Determining the battery shares is a key requirement for making a costs division and an economic analysis.

We assume that maximizing the self-consumption of solar power is the primary instrument of costs reduction. Since the model will operate under the assumption that feed-in power to the grid will not be reimbursed in the future, it is imperative that the injection of surplus PV-generated energy is minimized. Therefore, the optimal battery share is chosen according to statistics related to the maximum injection of surplus PV energy to the grid.

For each household, the injection distribution can be represented in a histogram. In order to determine the battery share, it is assumed that households need to be able to store their grid injected power a certain percentage of the time. Using a cumulative histogram, the grid injection at a certain percentage can be determined. The obtained level of grid injection for each household can subsequently be used to determine the required battery size according to the formula proposed in [24]:

$$Cap_{CES}^i = \frac{E_{grid,inj}^i}{(SoC_{max} - SoC_{min})\eta_{ch}}, \quad (1)$$

where  $E_{grid,inj}^i$  is determined based on known statistics of household  $i$  power injection to the grid.

With this formula, it is assumed that the battery capacity should be able to absorb the simultaneous occurrence of  $E_{grid,inj}^i$  for each household. Since the CES is assumed to be limited in size, the optimal battery size for each household may not be possible in the CES unit. Therefore, a share factor ( $Sh$ ) is proposed which can be used to allocate a part of the CES to each household according to its optimal battery share as follows:

$$Sh^i = \frac{Cap_{CES}^i}{\sum_{j \in N} Cap_{CES}^j}. \quad (2)$$

Alternatively, the optimal CES size can be determined using the following formula:

$$Cap_{CES,opt} = \sum_{i \in N} Cap_{CES}^i. \quad (3)$$

## 3. Optimization problem formulation

The main objective in the previously mentioned systems is to determine the minimal electricity costs when operating under a dynamic pricing tariff, while accommodating the constraints that are applicable to the systems. To optimize the performance of both systems, the problem is formulated using Mixed Integer Linear Programming (MILP) which consists of a linear function and a set of constraints with continuous and binary decision variables. MILP is a proven technique in mathematical optimization [25], and it has been successfully used to solve similar problems in this area of study [14,16,18,20].

### 3.1. Problem formulation: Scenario I

Objective function:

In this scenario, the HEMS in each household aims to minimize the amount of power absorbed from the main grid over a horizon of  $T$  time-slots. Therefore, the objective function of household  $i$  can be defined as:

$$\text{minimize} \sum_{t=1}^T c^t p_{grid,abs}^{t,i} \Delta t, \quad (4)$$

which implies taking benefit from the locally harvested solar energy  $P_{pv}^{t,i}$ , as well as from the scheduled energy in the battery  $p_{bat,dis}^{t,i}$  (see Eq. (5)).

Constraints:

#### 3.1.1. Local balance

In order to ensure the balance between power supply and demand for each household at each time-slot, the following constraints are used:

$$p^{t,i} = p_{sl}^{t,i} + P_{nsl}^{t,i} - P_{pv}^{t,i}, \quad \forall i, t, \quad (5)$$

where:

$$p^{t,i} = (p_{grid,abs}^{t,i} - p_{grid,inj}^{t,i}) + (p_{bat,dis}^{t,i} - p_{bat,ch}^{t,i}), \quad \forall i, t. \quad (6)$$

#### 3.1.2. Power boundaries

The power absorbed from and injected to the main grid, as well as the power charges and discharges the battery for household  $i$ , are bounded as follows:

$$0 \leq p_{grid,abs}^{t,i} \leq P_{grid,max}^i, \quad \forall t, i, \quad (7)$$

$$0 \leq p_{grid,inj}^{t,i} \leq P_{grid,max}^i, \quad \forall t, i, \quad (8)$$

$$0 \leq p_{bat,ch}^{t,i} \leq P_{bat,max}^i, \quad \forall t, i, \quad (9)$$

$$0 \leq p_{bat,dis}^{t,i} \leq P_{bat,max}^i, \quad \forall t, i, \quad (10)$$

These constraints ensure that the power absorbed from the battery or the grid does not exceed the physical capacities of the installed

cables.

### 3.1.3. Energy storage system

The battery SoC at time-slot  $t$  in  $i$  can be represented in the following constraint:

$$\text{SoC}^{t,i} = \text{SoC}^{t-1,i} - \left( \frac{1}{\eta_{\text{dis}} C_{\text{bat,HES}}^i} (p_{\text{bat,dis}}^{t,i}) \Delta t - \frac{\eta_{\text{ch}}}{C_{\text{bat,HES}}^i} (p_{\text{bat,ch}}^{t,i}) \Delta t \right), \quad \forall t. \quad (11)$$

The SoC of the battery is bounded as follows:

$$\text{SoC}_{\text{min}} \leq \text{SoC}^{t,i} \leq \text{SoC}_{\text{max}}, \quad \forall t. \quad (12)$$

Besides, a global balance of the battery should be included to ensure equal or better conditions for the next day.

$$\sum_{t=1}^T \text{SoC}^{t,i} - \text{SoC}^{t-1,i} \geq 0, \quad \forall t. \quad (13)$$

### 3.1.4. Shiftable appliances demand management

**3.1.4.1. Daily demand:** Each shiftable appliance can be scheduled for operation at certain time-slots. This constraint ensures that the total energy assigned to each appliance  $a$  per day fulfills its daily energy consumption requirement  $E_{\text{sl}}^a$ .

$$\sum_{t=1}^T p^{a,t,i} \Delta t = E_{\text{sl}}^a, \quad \forall a,i, \quad (14)$$

**3.1.4.2. Hourly demand:** The total hourly power demand of all appliances in household  $i$  at a certain time slot  $t$  should be equal to the shiftable appliances power demand.

$$\sum_{a=1}^{A^i} p^{a,t,i} = P_{\text{sl}}^{t,i}, \quad \forall t,i. \quad (15)$$

**3.1.4.3. Power boundaries:** Each appliance has lower and upper power limits which represent the minimum and maximum power requirement an appliance needs to operate properly.

$$P_{\text{min}}^a y^{a,t,i} \leq p^{a,t,i} \leq P_{\text{max}}^a y^{a,t,i}, \quad \forall a,t,i, \quad (16)$$

**3.1.4.4. Peak signal:** The following constraint ensures that the load of household  $i$  does not exceed the maximum allowed power signal at a certain time-slot.

$$p_{\text{sl}}^{t,i} + p_{\text{nsI}}^{t,i} \leq P_{\text{peak}}^{t,i}, \quad \forall a,i, \quad (17)$$

**3.1.4.5. Consumer preference:** Consumers are assumed to be able to determine the time window in which an appliance  $a$  is allowed to operate.

$$y^{a,t,i} \leq \text{CP}^{a,t,i}, \quad \forall a,i, \quad (18)$$

**3.1.4.6. Uninterruptible operation:** The following set of constraints ensure an appliance remains on for a certain period of time once it has started.

$$z^{a,i} = y^{a,t,i} - y^{a,t-1,i} \quad \forall t,a,i, \quad (19)$$

$$y^{a,t:r^a,i} \geq z^{a,i} \quad \forall t,a,i, \quad (20)$$

## 3.2. Problem formulation: Scenario II

The HEMS in scenario II has the same problem formulation in scenario I. The only difference is that each household is allocated a certain

share of the CES (see Section 2.4). Unless described otherwise, all constraints in problem formulation of scenario I are applicable in scenario II.

### 3.2.1. Battery state of charge

The SoC constraint is slightly modified. Where in scenario I each household is equipped with the same battery, the battery size for each household in scenario II is based on the battery share (Sh<sup>*i*</sup>) described in the previous section. Like in scenario I,  $C_{\text{bat,CES}}^i$  represents the battery share size of the CES allocated to household  $i$ . Based on each household' battery share (Sh<sup>*i*</sup>) and the total battery size of the CES (Cap<sub>CES</sub>), the  $C_{\text{bat,CES}}^i$  of each household is determined as:

$$C_{\text{bat,CES}}^i = \text{Sh}^i \text{Cap}_{\text{CES}}, \quad (21)$$

And the battery SoC dynamics constraint becomes as follows:

$$\text{SoC}^{t,i} = \text{SoC}^{t-1,i} - \left( \frac{1}{\eta_{\text{dis}} C_{\text{bat,CES}}^i} (p_{\text{bat,dis}}^{t,i}) \Delta t - \frac{\eta_{\text{ch}}}{C_{\text{bat,CES}}^i} (p_{\text{bat,ch}}^{t,i}) \Delta t \right), \quad \forall t, \quad (22)$$

### 3.2.2. Power boundaries

In order to ensure the battery charging and discharging power from the CES do not exceed the capacity of the cables, the following boundaries are proposed:

$$0 \leq p_{\text{bat,ch}}^{t,i} \leq \text{Sh}^i P_{\text{bat,max}}, \quad \forall t, \quad (23)$$

$$0 \leq p_{\text{bat,dis}}^{t,i} \leq \text{Sh}^i P_{\text{bat,max}}, \quad \forall t, \quad (24)$$

## 4. Economic indicators

The output of the optimization framework allows to determine the economic feasibility of the different scenarios. To do that, several economic indicators can be used. The Levelized Costs Of Energy (LCOE) is widely used as an index of the economic performance of battery systems [26,24,17]. In this paper, the LCOE represents the average costs of a unit of energy power demand over the systems' lifetime. Additionally, the Payback Period (PBP) is used to indicate the amount of time it will take to earn back the investment. When the PBP is larger than the systems' lifetime, the project is considered as economically infeasible.

The LCOE can be calculated to determine the average price of electricity with and without using ESS. When no ESS exists, the LCOE simply represents the average costs of power, since there is no investment. The investment costs of the PV installation are the same in each scenario, and since this paper is aimed at the economic performance of ESS, they are left out of this analysis. The yearly costs of electricity in household  $i$  are determined by taking the sum of the costs of power absorbed from the grid at each time-slot  $t$  as follows:

$$c_{\text{annual}}^i = \sum_{t=1}^{8760} c^t p_{\text{grid,abs}}^{t,i} \Delta t. \quad (25)$$

where 8760 is the number of hours in a year (24 \* 365) and  $\Delta t$  represents one hour.

### 4.1. Scenario I: HES

The LCOE of scenario I can be determined by adding the investment costs of HES, which is assumed to be the same for each household. To obtain the LCOE, the following formula is proposed:

$$\text{LCOE}^i = \frac{I_{\text{HES}} + \sum_{l \in L} c_{\text{annual}}^l / (1 + \gamma)^l}{\sum_{l \in L} (p_{\text{sl}}^{l,i} + P_{\text{nsI}}^{l,i}) / (1 + \gamma)^l}, \quad (26)$$

The PBP is described as the number of years needed to recover the

costs of investments through savings directly caused by the investment. Subsequently, the following formula is proposed:

$$PBP_{HES}^i = \frac{I_{HES}}{S^i}, \quad (27)$$

#### 4.2. Scenario II: CES

In scenario II, it is assumed that each household will pay the investment costs for its allocated battery share. The LCOE for each household is calculated in a similar way to scenario I as follows:

$$LCOE^i = \frac{Sh^i I_{CES} + \sum_{i \in L} C_{annual} / (1 + \gamma)^i}{\sum_{i \in L} (P_{si}^{t,i} + P_{nsi}^{t,i}) / (1 + \gamma)^i}, \quad (28)$$

The PBP is calculated in a similar fashion to scenario I, with the addition of the battery share:

$$PBP_{CES}^i = \frac{Sh^i I_{CES}}{S^i}, \quad (29)$$

### 5. Numerical results

#### 5.1. Case study

In our numerical evaluation, we use input data from real demand and PV generation profiles of  $N = 39$  households, obtained from the pilot project 'Jouw Energie Moment' (JEM). This project was initiated by the Dutch DSO 'Enexis' in looking for a solution to the rise of intermittent DERs, causing grid imbalance and threatening the continuity of the electricity supply in their grids. The first phase of JEM project (JEM1.0) was launched in January 2012 and ran until January 2015. Several households in Breda, the Netherlands, were equipped with a smart meter, a solar PV system, and a smart appliance (i.e., a smart washing machine). Households in this project are characterized as 'all-electric', which means that heating demand is included in their demand profile [27,28].

Since November 2016, the second phase of JEM project (JEM2.0) has entered the operational phase. JEM2.0 takes place in the same location of JEM1.0. In addition to the smart meter, HEMS, solar PV system and smart washing machine, households in JEM2.0 are equipped with a Tesla Powerwall as a HES to store the energy produced by their solar panels. Additionally, testing with a CES unit, is currently taking place in Etten-Leur, the Netherlands. Since JEM2.0 is still in its operational phase during this research, the project lacked usable data. Therefore, a combination of JEM1.0 and JEM2.0 data is used. Data from JEM1.0 will be used for the load and PV generation profiles since this pilot group is also included in JEM2.0.

Since the research is based on two different scenarios of ESS, the batteries are modelled to resemble the batteries employed in the JEM 2.0 project. Both the HES (i.e., scenario I) and the CES (i.e., scenario II) are modelled and simulated to minimize the cost of power absorbed from the grid. For scenario I, two HES units are modelled: the Powerwall 1 (S1PW1), currently being used in JEM2.0, and the more recent Powerwall 2 (S1PW2). For scenario II, the first unit used has a similar characteristics to the CES unit currently operating in JEM2.0 (S2CES). Additionally, a fictional battery (S2CES<sub>opt</sub>) will also be modelled which represents the optimal battery size determined by Eq. (3). By doing so, the aim is to provide additional insights on the economic benefits for households using a CES or HES. Finally, a baseline scenario is introduced which represents model operations where no ESS is installed. The characteristics and parameters value for every scenario is presented in Table 1. District capacity represents the total installed storage capacity for the pilot group, which equals the CES storage capacity in scenario II. In scenario I, it represents the sum of all installed HESs for  $N$  households. The HES storage capacity is identical for each household, therefore the average capacity equals the HES storage

capacity in scenario I. In scenario II it represents the average battery share per household. For calculating the shares in scenario II, we assume that households are able to store their grid injection 90% of the time. Using a cumulative histogram of the history of daily power injection of each household, the grid injection at 90% can be determined. The obtained level of grid injection can subsequently be used to determine the required battery size in Eq. (1).

In order to solve the models of two scenarios, the MILP problems are formulated in MATLAB (R2016B) using YALMIP toolbox [29], and solved using IBM ILOG CPLEX Optimization Studio [30]. The execution period is performed day-ahead from 00:00 till 24:00, where the cycle of the day is divided into  $T = 24$  time slots (i.e., every hour). The models are run and the costs are minimized over a time period of one year (i.e., 8670 h). Similar to the pilot implementation, one shiftable appliance (i.e., smart washing machine) is used in obtaining the results. Nevertheless, we stress that the model setup is capable of handling more than one shiftable appliance. For every scenario, it is assumed that the scheduling of the smart washing machine and the battery systems is done with 'perfect knowledge' about the demand and generation profile of each household. This assumption is reasonable for this work because the main aim is to analyze the economic potential of both storage scenarios over a time period of one year. Analysis of the consumer preference data from the JEM project showed that the washing machine is allowed to operate at each time-slot. Therefore, in order to simulate reality as accurately as possible, CP in Eq. (18) is set to 1 for every time-slot. For the dynamic electricity pricing tariff, we use the Real Time Pricing (RTP) scheme defined in [31], and used in JEM1.0 pilot project. The value of each parameter used in this simulation is provided in Table 1.  $P_{grid,max}^i$  has been chosen according to the actual design parameters of current grid configuration in the pilot group.  $P_{bat,max}^i$  for the HES is the same for each households,  $P_{bat,max}^i$  for the CES is allocated to households according to their battery share.  $SoC_{min}$  and  $SoC_{max}$  are equal for all considered battery systems.

#### 5.2. Annual overview

In Table 2, an overview of model results of different scenarios is presented. The average capacity represents the average battery size per household in the pilot group. It can be noticed that in all battery scenarios, both power injection and power absorption to and from the grid are smaller than the baseline scenario. As mentioned earlier, the annual average power demand and PV production are the same for each scenario.

When examining the results of S1PW1 and S2CES, it can be noted that the performance of S1PW1 on PV self-consumption is slightly larger compared to S2CES. This seems to be caused by the average battery size per household, which is larger in S1PW1. The results show that self-consumption of PV power can be increased between 23% and 29% in scenarios with storage. After a closer examination of the results of S1PW2 and S2CES<sub>opt</sub> on self-consumption, S2CES<sub>opt</sub> performs slightly

**Table 1**  
Configurations of different storage systems.

	S1PW1	S1PW2	S2CES	S2CES <sub>opt</sub>	Unit
District capacity	261	526	200	362	[kWh]
Average capacity (Cap)	6.7	13.5	5.1	9.2	[kWh]
$P_{bat,max}^i$	3.3	5	200	300	[kW]
$P_{grid,max}^i$			6.5		[kW]
$SoC_{min}$			25		[%]
$SoC_{max}$			90		[%]
$SoC_0$			50		[%]
$\eta_{ch} = \eta_{dis}$			0.95		[-]
$E_{sh}^{WM}$			1.34		[kWh]
$P_{min}^{WM} = P_{max}^{WM}$			0.67		[kW]

**Table 2**  
Average annual values (per household) of storage capacity, battery and grid operations and self-consumption.

	Annual average	Baseline	S1PW1	S1PW2	S2CES	S2CES <sub>opt</sub>	Unit
Model input	District capacity	0	261	526	200	362	[kWh]
	Average capacity	0	6.7	13.5	5.1	9.2	[kWh]
	Annual PV production	2088	2088	2088	2088	2088	[kW]
	Power demand	6088	6088	6088	6088	6088	[kW]
Model output	Battery charge	0	1650	2804	1371	1923	[kW]
	Battery discharge	0	1337	2531	1110	1558	[kW]
	Grid absorption	4710	4497	4404	4481	4475	[kW]
	Grid injection	710	183	130	219	110	[kW]
	PV self-consumption	0.67	0.92	0.94	0.9	0.95	[-]
	Self-consumption increase	0	26	28	23	29	[%]

better with a smaller district and average battery capacity. This can be explained due to the optimization of battery shares based on surplus PV power in S2CES<sub>opt</sub>.

### 5.3. Household operation

In order to show household operations, an arbitrary household is chosen from the dataset for the baseline, S1PW1 and S2CES scenarios to serve as an example. The battery share of this particular household is calculated using Eq. (2) to be 2.5 [kWh] in S2CES. The mechanics displayed in this section are applicable to each individual household.

In Fig. 2(a) and (b), the household demand profile without a battery is illustrated for an arbitrary week in different annual periods (i.e., January and June 2014, respectively). Power absorption and injection to the grid is shown in blue (i.e. negative for grid injection and positive for absorption), while the PV production is shown in pink.

The same household operation is shown after implementing a Powerwall 1 in Fig. 2(c) and (d), and allocating a battery share in the CES in Fig. 2(e) and (f), in winter and summer, respectively. The battery charging and discharging power is shown in red (i.e. negative for charging and positive for discharging). It can be observed that the charging of the battery is more 'violent' during winter, when the PV production is low. This can be observed in the SoC dynamics. The battery will often charge completely during one or two time-slots, when the price is low, in order to discharge completely when prices are high. In summer, the power injected to the grid is severely reduced in S1PW1 and somewhat less in S2CES. This indicates that the battery size of S2CES is insufficient to provide the optimal storage size for this particular household. In both cases, the figure shows that the battery is less often charged from the grid, and is mostly charged by the surplus PV power. This is also visible in the SoC, which shows a much more irregular charging pattern.

### 5.4. Economic analysis

In Fig. 3, the average monthly costs per household are presented. The monthly costs are defined as the costs of the power from the grid in order to satisfy the power demand of household *i* during one month. It can be observed that the monthly costs are highest during winter for all scenarios. This can be explained by the 'all-electric' characteristics of the households demand which includes the electric heating. Furthermore, it can be noticed that the difference between the costs in the baseline scenario and scenario I and II, are larger during the summer. This can be explained by the assumption that grid injection is not reimbursed in the baseline scenario. Therefore, it can be concluded that storing surplus PV is the largest contributor to costs reductions obtained when using the battery systems.

The economic results of the baseline scenario, scenario I (S1PW1/S1PW2) and scenario II (S2CES/S2CES<sub>opt</sub>) are presented in Table 3. A nominal discount rate of 4% is used, which has been widely used in other studies such as [32]. The LCOE and PBP are calculated using Eqs.

(26)–(29). The investment costs of ESS are assumed to be 7000 [Euro] for S1PW1 and S1PW2, and 1000 [Euro/kWh] for S2CES and S2CES<sub>opt</sub> [33,34]. The results show that the LCOE in both scenario I and II, is higher compared to the baseline LCOE. This indicates that using battery storage will increase the costs made to satisfy power demand, which means that none of the battery systems are profitable in the current model setup. This is also clearly illustrated in the PBP, ranging from 26 to 43 years. The average electricity costs, like the annual savings, show that costs reductions, ranging from 22 to 30%, can be obtained with both HES and CES systems. The PBP's show that these savings are too small to recuperate the investment costs within the lifetime. When comparing the results from S1PW1 with S2CES, it can be noted that the savings are similar while having a smaller total installed storage capacity in S2CES (see Table 2). The system lifetime is assumed to be 10 years in every scenario [33,34]. This means that none of the systems are able to recuperate their investment costs within the system lifetime. However, the PBP in S2CES (26 years) is smaller than in S1PW1 (36 years).

### 5.5. Sensitivity analysis

Results from Table 3 shows that both the HES and the CES, under the configurations used in this research, are economically infeasible. A sensitivity analysis is conducted in this section to explore the influence of several parameters on the economic performance of each scenario. The results of the sensitivity analysis are all presented as district wide averages per household. The battery size for scenario I is varied from 2 to 20 [kWh], with steps of 2 [kWh], while the battery size of scenario II is varied from 50 to 800 [kWh], with steps of 50 [kWh]. Additionally, the maximum charge and discharge capacity are scaled relative to the battery sizes. We use S1PW1 as a HES in scenario I, and S2CES as a CES in scenario II. Finally, the investment costs per kWh are varied between 100 and 1000 [Euro/kWh] for both scenarios I and II. Every other parameter remained unchanged. The results are displayed in Figs. 4–8.

Fig. 5 illustrates the costs development for power demand with increasing battery size for both scenario I and II. The figure illustrates that both systems show the same behaviour. The concave character of the price development is related to the self-consumption of PV power (i.e., see Fig. 4). As the battery size increases, the self-consumption of PV power increases with it. However, the marginal effect of increasing battery size on self-consumption, decreases with each added kWh of storage. Therefore the marginal effect of increasing battery sizes on the power demand costs, also decreases. When self-consumption is no longer increasing, the decrease in power demand costs is created only by storing cheap energy for use when the price is high.

The annual savings for increasing battery sizes, both CES and HES, are presented in Fig. 6. Again, self-consumption has a large influence on the results. With increasing storage capacity, the marginal savings decrease. The total installed storage capacity in the HES scenario (i.e., the sum of the storage capacity of every household) is slightly larger compared to the storage capacity in the CES scenario (see Table 1). This

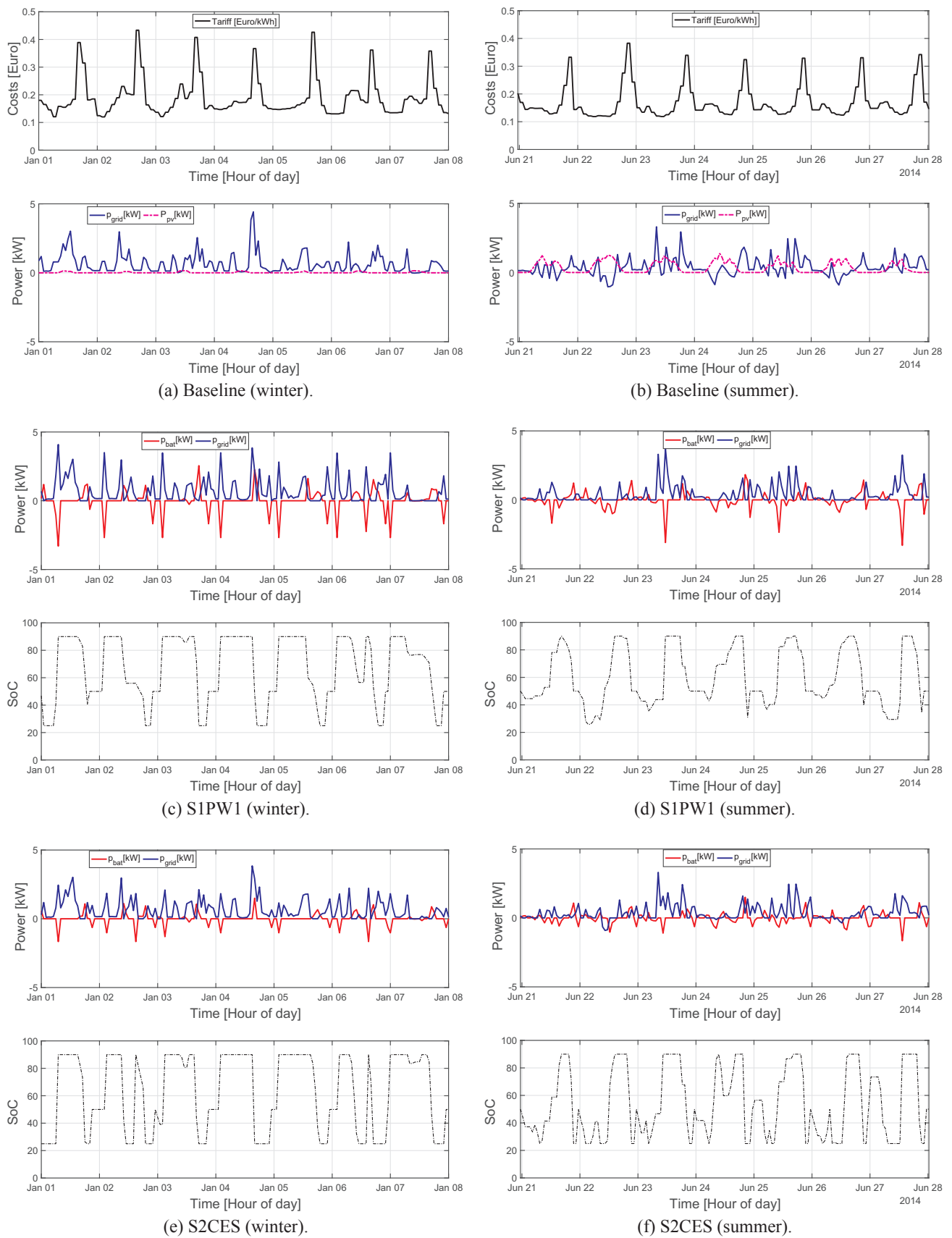


Fig. 2. Example of model operations of both scenarios in a single household during an arbitrary week and different annual periods.



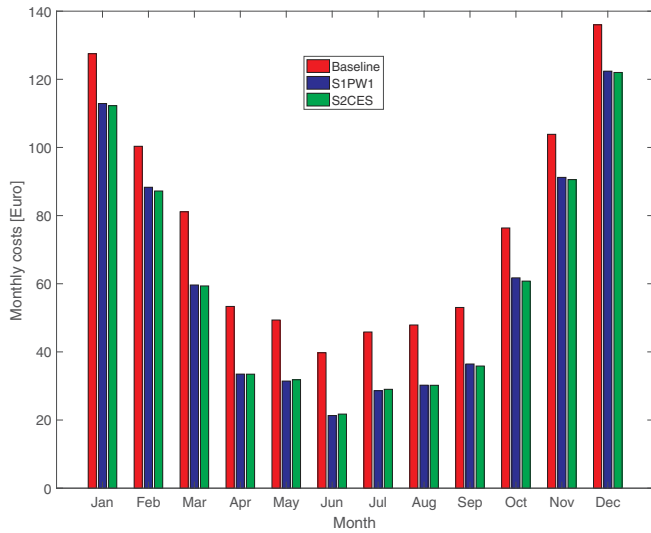


Fig. 3. Average monthly costs per household in the pilot group.

Table 3

Results on several economic parameters, all results are average annual values for a household in the pilot group.

Economic parameter	Baseline	S1PW1	S1PW2	S2CES	S2CES <sub>opt</sub>	Unit
LCOE ( $\gamma = 4\%$ )	0.1495	0.2626	0.2501	0.2403	0.3376	[Euro/kWh]
Electricity costs	0.1495	0.1161	0.1035	0.1156	0.1131	[Euro/kWh]
$I_{HES}/ShI_{CES}$	0	7000	7000	5128	9231	[Euro]
Annual costs	914	718	640	714	698	[Euro]
Annual savings	0	22	30	22	24	[%]
PBP	0	36	27	26	43	[years]

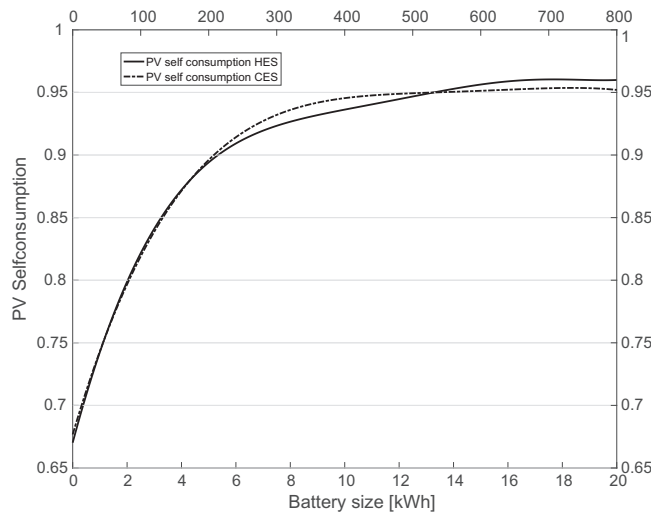


Fig. 4. PV self-consumption per household for CES and HES with variable battery size. The lower x-axis represents different HES system sizes, The upper x-axis represents different CES system sizes.

creates the appearance of larger savings when using HES systems.

Fig. 7 illustrates the PBP of different installations, both HES and CES, using different investment costs conditions (i.e. solid lines for HES and broken lines for CES). The results show that both systems react similarly on increasing investment costs and battery sizes. The horizontal black line represents the assumed system lifetime of 10 years. According to these results, all battery sizes, for both HES and CES

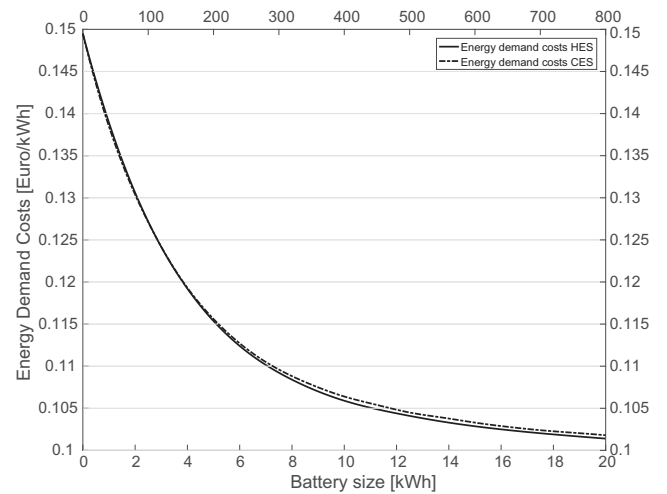


Fig. 5. Costs per kWh of power demand per household for CES and HES with variable battery size.

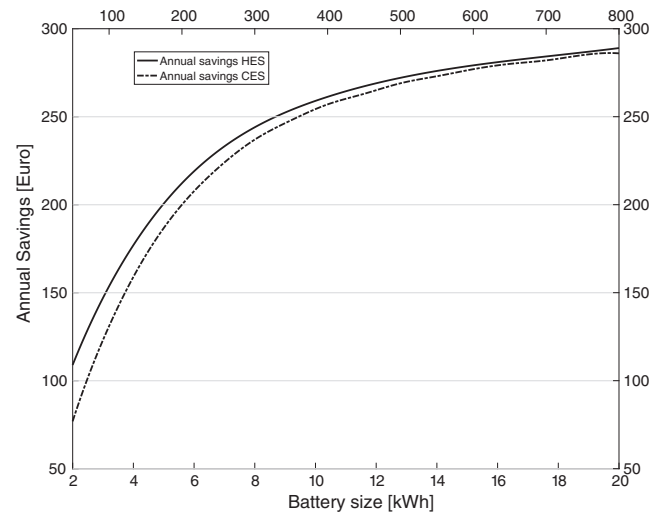


Fig. 6. Annual savings per household for CES and HES with variable battery size.

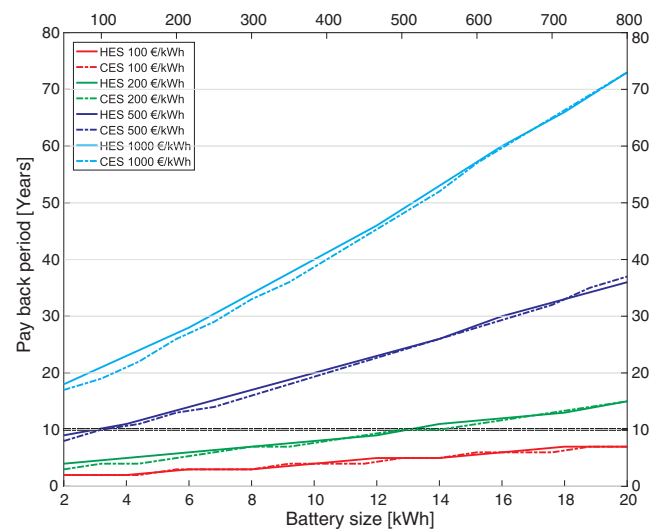


Fig. 7. Payback period for CES (broken line) and HES (solid line) with variable investment costs and battery size.

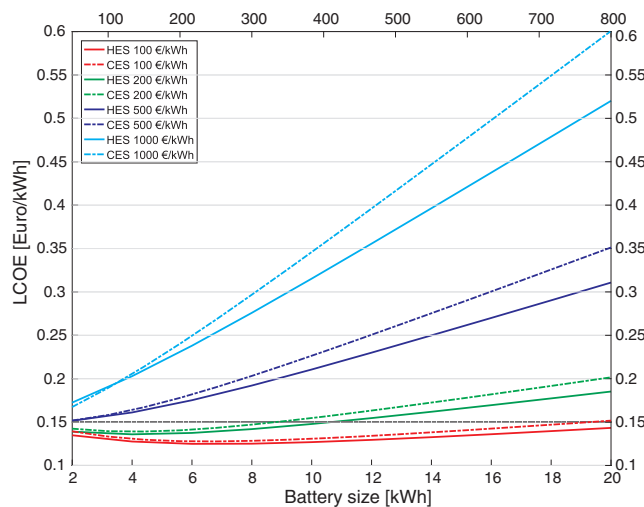


Fig. 8. LCOE for CES (broken line) and HES (solid line) with variable investment costs and battery size.

systems, are economically feasible when the investment costs are 100 [Euro/kWh]. If investment costs are 200 [Euro/kWh], HES systems up to 13 [kWh], and CES batteries up to 500 [kWh], will be recuperated within the system lifetime. When investment costs are 1000 [Euro/kWh], none of the battery sizes for both HES and CES systems are recuperated within the lifetime of the systems.

Fig. 8 illustrates the LCOE for both HES and CES systems. The horizontal black line represents the LCOE in the baseline scenario (i.e., without investment costs for the ESS). The results clearly show the influence of self-consumption of PV power, especially with investment costs of 100 and 200 [Euro/kWh]. The self-consumption of PV causes the LCOE's, when the investment cost is 100 and 200 [Euro/kWh], respectively, to decrease below baseline.

Fig. 8 also shows that, with increasing battery size, the LCOEs for CES systems are larger. This can be explained by definition of the LCOE used in this research. In Eqs. (26) and (28), the LCOE is defined as the investment and annual costs divided by the annual power demand. Therefore, households with a large PV surplus and a low power demand receive a large battery share, and subsequently, a large LCOE, which increases the average LCOE. This causes the LCOE results to be larger for scenario II, which can be misleading.

## 6. Discussions and future work

### 6.1. Results discussion

#### 6.1.1. Investment costs

The results in Section 5 shows that both CES and HES storage are not economically feasible for end-consumers. The sensitivity analysis results show that, in the current model setup, both HES and CES systems react similarly to changing battery sizes and investment costs. An important question that remains unanswered is how the investment prices (Euro/kWh) will develop in the future. Storage system investment costs consist of two components, battery and system costs. The production costs of batteries can be expected to decline in the future due to increasing demand. Price developments of EMSs might play a crucial role in the future of both HES and CES systems. In personal communication with ATEPS [33], a market party which develops and produces CES units, ATEPS expects the EMS costs for HES to decline much faster than CES units. An EMS for a CES has to communicate with multiple 'actors' and requires more advanced algorithms compared to HES systems. These systems are expected to be more expensive which will increase the total investment costs for CES units.

#### 6.1.2. Environmental and social benefits

CES units might perform better on environmental indicators such as CO<sub>2</sub> production and material usage. From the results of S1PW2 and S2CES<sub>opt</sub> in Table 2, it can be observed that both systems reach the same level of PV self-consumption, however the total installed capacity is much smaller in S2CES<sub>opt</sub>. This indicates that CES systems show potential in optimizing the battery share for each household individually. Therefore, it can be argued that CES systems can achieve larger costs savings with fewer resources. Further research should be done on the possible environmental benefits of CES systems compared to HES systems.

Another social benefit of CES systems might consider safety issues related to lithium-ion batteries. Lithium-ion batteries are known to pose a certain fire risk if installed incorrectly. By centralizing storage, individual installation of battery systems can be avoided. Therefore, reducing the risk to a single location instead of multiple locations.

### 6.2. Research shortcomings and assumptions

#### 6.2.1. No reimbursement

In the paper, it is assumed that the feed-in-tariff will disappear entirely in the future. The scenario used in this paper can therefore be seen as a 'best case' scenario for batteries since the incentive to use a battery to store PV power is very large. In reality, households will typically receive some reimbursement for the injected PV power. Therefore, it can be argued that the incentive to use ESS will be lower in real-life applications in the Netherlands. However, the use of batteries might be stimulated by the Dutch government through subsidies. From this follows that future policy decisions will have a large impact on the use of ESS by end-consumers in the Netherlands.

#### 6.2.2. Fixed battery shares based on grid injection

In the paper, it is assumed that households have fixed-size battery shares from the CES over time. This assumption was for reducing the complexity of the economic analysis. However, the battery share allocation can be optimized by using dynamic-size battery shares. More in depth research is required to investigate the possibility of additional economic benefits, when using dynamic battery shares allocation. In addition, battery shares are divided according to the maximum amount of grid injection per household. As observed in the results, this has an influence on the LCOE, by allocating large battery shares to households with large amount of surplus PV power but low power demand. The adoption of large PV installations in households can be explained by the currently favourable feed-in-tariffs conditions for surplus PV power in the Netherlands. However, installing a large battery to reduce the injection of surplus PV to the grid without taking the demand into account affects the economic feasibility in some households. Households with low power demand will not use the available energy in the battery, therefore it will remain charged and unable to capture the surplus PV in the next day. From this follows that the allocation of battery shares can be improved by also taking households power demand into account.

#### 6.2.3. Pricing scheme implications

The electricity prices used in this paper are predetermined using the RTP scheme. In reality however, several mechanics will have influence on the price. As we have seen in the results, adding battery systems to households, influences both power supply and demand. As more batteries are used in the market, more batteries will charge when prices are low. This increases demand, which increases the price at that time. This feedback loop may have a 'levelling' effect on the RTP scheme. This means that the price differences in the RTP scheme will decrease as more batteries are used.

Further research should be conducted using different price schemes. An example of an alternative scheme is the Adaptive Consumption Level Pricing Scheme (ACLPS) [35]. Tariffs such as the ACLPS are only influenced by the behaviour of the individual consumers and not by

externalities caused by others in the market. In future work, both HES and CES systems can be investigated using this scheme in order to determine the economic feasibility under a different pricing scheme.

#### 6.2.4. Combination of several business models

This research has shown that both HES and CES systems have a limited economic potential for end-consumers. ESS will only become feasible when investment prices drop sufficiently. Both HES and CES systems could also be deployed in order to serve the benefits of DSOs. ESS might be deployed to avoid grid congestion and they can also be installed to prevent grid reinforcement. If battery systems are going to be used for multiple ends, the investment costs should be divided among the actors involved in the exploitation of the system. Investment reductions or subsidies from third parties might serve to the improvement of the end-consumer business case in both HES and CES systems. Therefore, it is suggested that future work will focus on a combination of battery services in order to improve economic feasibility.

## 7. Conclusions

In this study, the economic feasibility of both HES and CES systems has been determined. Each system has been modelled with several battery types. CES systems are divided into fixed shares according to a statistical analysis of households' annual surplus PV power injection to the grid. In both scenarios, households aim to minimize the costs of power absorbed from the grid. Demand and generation profiles of 39 households in the JEM pilot projects initiated by the Dutch DSO "Enexis" are used as model input. A smart washing machine and the battery systems are subsequently scheduled under a RTP scheme.

Results show that under current investment costs of ESS per kWh, both HES and CES are economically infeasible for households. PV self-consumption has a large impact on annual saving achieved by ESS which subsequently influences the PBP. The ability to use a RTP scheme to absorb energy when the price is low adds relatively small benefits when increasing battery sizes. This suggests that both CES and HES systems are economically most efficient when used to increase the self-consumption of PV generation. The main driver behind the economic infeasibility of both systems is the investment costs per kWh of storage capacity. Further research has to be done on the development of the investment costs of both HES and CES systems, since these developments will likely determine which system will become dominant in the future. Future research should also include the combination of different business models in both HES and CES systems. Besides, other pricing schemes should be considered for the end-consumer. Finally, further investigation should be conducted in the optimization of battery shares allocation in CES.

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